

PROCEEDINGS B

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Journal:	<i>Proceedings B</i>
Manuscript ID	RSPB-2016-2290.R1
Article Type:	Research
Date Submitted by the Author:	n/a
Complete List of Authors:	Puttick, Mark; University of Bristol, Earth Sciences O'Reilly, Joseph; University of Bristol, School of Earth Sciences Tanner, Alastair; University of Bristol, Biological Sciences Fleming, James; University of Bristol, School of Earth Sciences Clark, James; University of Bristol, School of Earth Sciences Holloway, Lucy; University of Bristol, School of Earth Sciences Lozano-Fernandez, Jesus; University of Bristol, School of Earth Sciences Parry, Luke; University of Bristol, Life Sciences Building Tarver, James; University of Bristol, Earth Sciences Pisani, Davide; University of Bristol, School of Earth Sciences Donoghue, Philip; University of Bristol, School of Earth Sciences
Subject:	Evolution < BIOLOGY, Palaeontology < BIOLOGY, Taxonomy and Systematics < BIOLOGY
Keywords:	phylogeny, Bayesian, parsimony, morphology, palaeontology, Maximum Likelihood
Proceedings B category:	Palaeobiology

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Manuscripts

Uncertain-tree: discriminating among competing approaches to the phylogenetic analysis of phenotype data

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Abstract

Morphological data provides the only means of classifying the majority of life's history, but the choice between competing phylogenetic methods for the analysis of morphology is unclear. Traditionally, parsimony methods have been favoured but recent studies have shown that these approaches are less accurate than the Bayesian implementation of the Mk model. Here we expand on these findings in several ways: we assess the impact of tree shape and maximum-likelihood estimation using the Mk model, as well as analysing data composed of both binary and multistate characters. We find that all methods struggle to correctly resolve deep clades within asymmetric trees, and when analysing small character matrices. The Bayesian Mk model is the most accurate method for estimating topology, but with lower resolution than other methods. Equal weights parsimony is more accurate than implied weights parsimony, and Maximum Likelihood estimation using the Mk model is the least accurate method. We conclude that the Bayesian implementation of the Mk model should be the default method for phylogenetic estimation from phenotype datasets, and we explore the implications of our simulations in reanalysing several empirical morphological character matrices. A consequence of our finding is that high levels of resolution or the ability to classify species or groups with much confidence should not be expected when using small datasets. It is now necessary to depart from the

20 traditional parsimony paradigms of constructing character matrices, towards datasets
21 constructed explicitly for Bayesian methods.

22

23 **Keywords:** phylogeny, Bayesian, parsimony, cladistics, morphology, palaeontology

24 **1. Introduction**

25

26 The fossil record affords the only direct insight into evolutionary history of life on
27 Earth, but the incomplete preservation and temporal distribution of fossils has long
28 prompted biologists to seek alternative perspectives, such as molecular phylogenies of
29 living species, eschewing palaeontological evidence altogether [1]. However, there is
30 increasing acceptance that analyses of historical diversity cannot be made without
31 phylogenies that incorporate fossil species [2,3] and calibrating molecular
32 phylogenies to time cannot be achieved effectively without recourse to the fossil
33 record [4]. Integrating fossil and living species has become the grand challenge and
34 there has been a modest proliferation of phylogenetic approaches to the analysis of
35 phenotypic data. While conventional parsimony remains the most widely employed
36 method, alternative parsimony [5] and probabilistic [6] models have been developed
37 to better accommodate heterogeneity in the rate of evolution among characters and
38 across phylogeny. Unfortunately, these competing methods invariably yield disparate
39 phylogenetic hypotheses among which it is difficult to discriminate since the true tree
40 is never known for empirical data.

41

42 A number of studies have attempted to establish the efficacy of competing
43 phylogenetic methods using data simulated from known trees [7–9], finding that the
44 probabilistic Mkv model outperforms parsimony methods, among which,
45 conventional equal-weights parsimony performs best. However, these studies were
46 potentially biased by their experimental design: (i) two of the studies employed a
47 generating tree that was unresolved and, therefore, biased against parsimony methods
48 which recover resolved trees; (ii) these studies did not discriminate between the
49 impact of the probabilistic model and its implementation in a Bayesian framework;
50 (iii) based on single empirical trees, the impact of tree symmetry, which is known to
51 confound phylogeny estimation [10], was not explored; (iv) only binary characters
52 were considered, whereas empirical datasets are commonly a mixture of binary and
53 multistate characters. Therefore, we compare the performance of equal-weights
54 parsimony (EW-Parsimony), implied-weights parsimony (IW-Parsimony), Maximum
55 Likelihood and Bayesian implementations of the Mk model, based on datasets with
56 different numbers of characters, comprised of binary and multistate characters and
57 simulated on a fully balanced and a maximally-imbalanced phylogenetic tree. We find

that Bayesian inference out-performs all other methods, while EW-Parsimony performs better than IW-Parsimony, and Maximum Likelihood performs worst of all. We apply these competing phylogenetic methods to empirical morphological datasets of similar sizes to our simulated datasets and explore the efficacy of the ensuing phylogenetic hypotheses in light of the conclusions derived from our simulation-based study.

2. Materials and Methods

(a) Simulation of Morphological Matrices

We simulated data on two 32-taxon generating trees at the extremes of tree symmetry: one fully asymmetrical and one fully symmetrical (see Supplementary Fig S1). For each tree we simulated matrices of three sizes: 100, 350 and 1000 characters. We generated matrices using the HKY + Γ Continuous model of molecular substitution, with $\kappa = 2$, the shape (set equal to rate) of the gamma distribution and underlying substitution rate for each replicate sampled from independent and identically distributed exponential distributions with a mean of one, and character state stationary frequencies fixed as $\pi = [0.2, 0.2, 0.3, 0.3]$. We used a fixed and uneven stationary distribution of nucleotide frequencies to ensure our simulation model did not collapse into the Mk model, as this would bias the analysis in favour of Mk model-based approaches. We simulated 1000 replicate matrices with unique substitution parameters for each tree and each character number, resulting in a total of 6000 matrices. We set two types of character within each matrix, binary and multistate, and we simulated a proportion of 55 binary:45 multistate characters, based on the mean ratio found in a survey of empirical morphological data matrices [11]. We established binary characters by converting data simulated under the HKY model to R/Y coding (i.e. 0/1): morphological multistate characters were simulated by converting DNA bases to integers.

To ensure that our simulated data are realistic, we generated each set of 1000 unique replicate matrices such that the among-matrix distribution of homoplasy approximated the distribution of empirical homoplasy, characterised by the Consistency Index (CI), reported by Sanderson and Donoghue [12]. To approximate this distribution of homoplasy we placed the Sanderson and Donoghue data into

quantised bins of CI spanning 0.05, between the empirical bounds of 0.26 and 1.0, and simulated matrices until we matched this expected density per bin (Supplementary Figure S2).

95

The code used to simulate these data is available in Electronic Supplementary Materials.

98

(b) Phylogenetic analysis

We analysed the simulated matrices with EW-Parsimony, IW-Parsimony (k=2), and the Mk model [6] under both Maximum Likelihood and Bayesian implementations. EW-Parsimony and IW-Parsimony estimation of topology was performed in TNT [13]. We used the Mk plus gamma model for Maximum Likelihood estimation of topology in RAxML 7.2 [14], and Bayesian estimation of topology in MrBayes 3.2 [15]. As the approximate likelihood calculation of RAxML may be distant from the true likelihood [16], we conducted a sensitivity test by re-analysing a subset of our data with the likelihood implementation of the MK model in IQ-tree [17]; both methods gave effectively identical results, indicating results from the likelihood MKv model are not software-specific.

110

The Mkv model is inappropriate due to the lack of acquisition bias in the simulated data. For both Maximum Likelihood and Bayesian analyses we applied the discretised gamma distribution model to account for between-character rate heterogeneity. For Bayesian analyses the posterior distribution was sampled one million times by four chains using the Metropolis-coupled Markov-chain Monte Carlo algorithm, two independent runs were performed for each replicate and the two resulting posterior samples were combined after qualitative assessment of convergence. For parity, we characterised the result of all phylogenetic methods as the majority-rule consensus of resultant tree samples. We did not employ bootstrap methods to measure support for parsimony and likelihood analyses because phenotypic data does not meet the assumption that phylogenetic signal is distributed randomly among characters.

122

We used the Robinson-Foulds metric [18] to compare the similarity of estimated topologies against their respective generating tree. We also noted the per-node resolution, and the variation of node accuracy across the topology.

126

127 (c) Empirical analyses

128 We analysed four published palaeontological phenotype character matrices that
129 encompass a range of character numbers and a diverse sample of taxa from the Tree
130 of Life [19–22]. We resolved any ambiguities in character coding to their most
131 derived state for each matrix to make analyses compatible across the different
132 phylogenetic methods, facilitating comparison of results. We analysed each matrix by
133 applying the same settings used to analyse our simulated matrices: EW-Parsimony,
134 IW-Parsimony, as well as Bayesian and Maximum Likelihood implementations of the
135 Mk model. Empirical morphological matrices are rarely constructed to contain
136 invariant or parsimony uninformative characters. Therefore, the Mkv extension of the
137 Mk model, which uses conditional likelihood to correct for such acquisition biases, is
138 more appropriate than the Mk model for analysis of these empirical data matrices [6].

139

140 **3. Results**

141

142 (a) Simulated data

143 Accuracy is higher for trees inferred from data simulated on a symmetrical topology
144 compared to trees estimated from data simulated on the asymmetrical topology
145 (compare figures 2, 3). Bayesian consensus phylogenies are generally the least well
146 resolved (Figure 1). All methods estimated topologies with greater accuracy as the
147 number of analysed characters increased (figs 2, 3; supplementary table S5-7). All
148 methods, apart from Maximum Likelihood, produced phylogenies with greater
149 resolution with higher numbers of characters (figure 1).

150

151 For all implementations and dataset sizes, the Bayesian implementation of the Mk
152 model achieves higher accuracy compared to other methods (table 1; figs 1-3). The
153 two parsimony methods achieved the next highest levels of accuracy, EW-Parsimony
154 achieving greater accuracy than IW-Parsimony. Maximum Likelihood was the least
155 accurate method for topology reconstruction for both the symmetrical and
156 asymmetrical phylogenies (table 1). The relative accuracy of these phylogenetic
157 methods remains the same across all dataset sizes and the two simulation topologies
158 (table 1; figs 1-3).

159

Nodes closer to the tips are significantly more accurately reconstructed in the asymmetrical phylogenies across all dataset sizes (table 2; figure 2; supplementary figure S8). In the symmetrical trees, there was no significant correlation between distance from the tips and the accuracy of node reconstruction, except in the Maximum Likelihood analysis of 100 characters (figure 2; table 2).

(b) Empirical phylogenies

Patterns of resolution achieved from the simulated datasets are similar for the empirical datasets. The Bayesian implementation of the Mk model estimates the least resolved phylogenies and Maximum Likelihood produces fully-resolved trees (full trees are shown supplementary figure S9-15).

Kulindroplax, from the Sutton et al. [22] dataset, is supported as a crown-mollusc based on Maximum Likelihood, EW-Parsimony, and IW-Parsimony (figure 4a-d). The results of the IW-Parsimony analysis are most similar to the original results [22], with *Kulindroplax* resolved as a crown-aplacophoran; Maximum Likelihood analysis of the dataset resolved *Kulindroplax* as the stem-aplacophoran. The result of the Bayesian analysis of the dataset is largely unresolved, and *Kulindroplax* is not discriminated as a member of any clade within molluscs or even as a member of total-group Mollusca.

The anthophyte hypothesis (non-monophyletic gymnosperms sister to seed ferns plus angiosperms) recovered by Hilton and Bateman [19] is supported by our EW-Parsimony and Maximum Likelihood analyses of their dataset which recovered a paraphyletic seed ferns plus Gnetophyta as sister to angiosperms (figure 4f, g); the results of Bayesian and IW-Parsimony analyses of the same dataset contradict the anthophyte hypothesis (figure 4e, h). The Bayesian analysis produced a non-monophyletic gymnosperms with the relationships between them and seed ferns unresolved with the exception of *Bennettitales* which resolved as a gnetophyte, and *Caytonia* as sister to the angiosperms.

Analyses of the Luo et al. [20] dataset yielded congruent results with the original study, with the placement of *Haramiyavia* outside of crown Mammalia and

193 multituberculates, although some haramiyids are resolved as crown mammals in the
194 IW-Parsimony analysis (figure 5a-d).

195

196 *Nyasasaurus* is recovered as a member of Dinosauria in the Maximum Likelihood,
197 EW-Parsimony, and IW-Parsimony analyses of the dataset from Nesbitt et al. [21]
198 (figure 5e-h). The Bayesian analysis recovers *Nyasasaurus* in a polytomy with the
199 two major clades of dinosaurs, corroborating the conclusion of Nesbitt et al. [21] that,
200 given the data, its precise phylogenetic position is uncertain.

201

202 **4. Discussion**

203

204 **(a) Simulations indicate that the Bayesian implementation of the Mk model out-** 205 **performs all other methods and implementations**

206 Previous simulation-based analyses that have attempted to evaluate the performance
207 of likelihood and parsimony-based phylogenetic methods for analysing phenotypic
208 data have found that the probabilistic model performs best [7,8]. However, these
209 studies were biased against parsimony because they employed an unresolved
210 generating tree that is problematic since parsimony methods will attempt to recover a
211 fully resolved tree from the simulated data yielding a non-zero RF distance from the
212 generating tree, even if the two trees are effectively compatible. Furthermore, since
213 previous simulation studies considered the Mk model only within a Bayesian
214 framework, they did not distinguish between the impact of the probabilistic model of
215 character evolution and the statistical framework in which it was implemented.

216

217 Our analyses control for these shortcomings of previous simulation studies and show
218 consistently that the Bayesian implementation of the Mk model performs best. In line
219 with previous simulations [8], we found that EW-Parsimony performs better than IW-
220 Parsimony. There is overlap between model performance shown by the distribution of
221 Robinson-Foulds distances (table 1), but there is reason to have different degrees of
222 confidence in the models; only the Bayesian implementation produces a relatively
223 small distribution of tree performance compared to the large tails signifying worse
224 performance in the two parsimony methods (table 1). We also found that the Bayesian
225 implementation of the Mk model outperforms the Maximum Likelihood
226 implementation, indicating that it is not merely the probabilistic transition model that

227 outperforms parsimony methods, but the implementation of the Mk model within a
 228 Bayesian statistical framework. Indeed, the Maximum Likelihood implementation of
 229 the Mk model was the worst-performing method, worse even than IW-Parsimony. In
 230 part, the poor performance of the Maximum Likelihood-Mk method is because we did
 231 not capture phylogenetic uncertainty associated with this phylogenetic method. This is
 232 normally achieved in analyses of molecular datasets through bootstrapping methods,
 233 but these are inappropriate for the analysis of phenotypic data since the basic
 234 methodological assumption, that the phylogenetic signal is randomly distributed
 235 across sites (characters), is not true for morphological data.

236

237 However, irrespective of the phylogenetic method used, dataset size correlated
 238 positively with both phylogenetic accuracy and resolution, diminishing differences in
 239 the relative performance of the competing phylogenetic methods. All phylogenetic
 240 methods also performed best when attempting to recover a symmetrical target tree; all
 241 methods found recovery of asymmetrical trees challenging and phylogenetic accuracy
 242 diminished from tip to root. The impact of tree topology is of particular concern since
 243 empirical phylogenetic trees are invariably asymmetric [23], and trees of fossil
 244 species are infamous for their asymmetry [24,25]. However, there is a broad spectrum
 245 of tree symmetry, with fully symmetric and fully asymmetric trees representing end-
 246 members. Palaeontological trees with the dimensions used in our simulations are
 247 typically far from the fully asymmetric pectinate generating tree we employed ($I_c =$
 248 ~ 0.4 for 32 species) [25]. Furthermore, the asymmetry of many palaeontological trees
 249 is often a representational artefact of attempting to summarise character evolution, or
 250 an analytic artefact of analysing the relationships among diverse clades based on
 251 representative species or higher taxa [26]. Thus, the challenge of recovering trees of
 252 extinct taxa may not be as great as a simplistic interpretation of our results might
 253 suggest.

254

255 **(b) Analyses of empirical data bear out conclusions based on simulations**

256 Maximum Likelihood, IW-Parsimony and EW-Parsimony methods of the simulated
 257 datasets commonly identify a single optimal tree, but the differences between the
 258 optimal trees derived from these methods provides no confidence that any one of the
 259 inferred topologies is accurate with reference to the placement of a taxon of interest.
 260 This view is corroborated by our reanalysis of empirical datasets which recovered

261 poorly resolved trees using the Bayesian implementation of the Mk model, and in a
262 number of instances, indicate that the conclusions drawn in the corresponding original
263 studies are not supported by the data.

264

265 In an extreme example, our re-analyses of the dataset published by Sutton et al. [22],
266 which attempted to demonstrate a crown-aplacophoran mollusc affinity for
267 *Kulindroplax*, yielded disparate hypotheses of affinity. EW-Parsimony and IW-
268 Parsimony recovered the published result, while Maximum Likelihood recovered
269 *Kulindroplax* as a stem-aplacophoran, and Bayesian could not discriminate
270 *Kulindroplax* as a total-group mollusc (figure 4a). This poor resolution is unlikely to
271 be a result of poor fossil evidence but, rather, the lack of discriminatory power in the
272 small character matrix. Among the analyses of the dataset from Hilton and Bateman
273 [19] we recovered some of the principal competing topologies that have featured in
274 debate over the affinity of seed plants in past decades. However, the Bayesian
275 analysis of the dataset recovered a topology that is largely unresolved in terms of the
276 relationships among key clades. This suggests that the available data are insufficient
277 to discriminate among the competing hypotheses, and this long-standing debate is
278 largely an artefact of the false resolution of parsimony methods.

279

280 Bayesian analyses need not overturn the results from previous analyses based on
281 deterministic phylogenetic methods like EW-Parsimony, IW-Parsimony, and
282 Maximum Likelihood. A phylogenetic position for haramiyids, outside crown-
283 Mammalia, is corroborated by our Bayesian analysis of the dataset from Luo et al.
284 [20] - in contrast to the crown-Mammalia affinity recovered for some haramiyids
285 through IW-Parsimony analysis of the same data (figure 5d). Similarly, *Nyasasaurus*
286 was posited as the earliest dinosaur, and this conclusion is supported by the Bayesian
287 analyses (Figure 5e) although this is not supported by EW-Parsimony, IW-Parsimony,
288 and Maximum Likelihood analyses (Figure 5f-h). However, the Bayesian analysis is
289 more robust in expressing the phylogenetic ambiguity identified by the original
290 authors [19], as *Nyasasaurus* falls in a polytomy alongside the two major clades of
291 dinosaurs.

292

293 Some of the differences between methods may simply reflect the dimensions of the
294 dataset. The two datasets that cannot resolve relationships under Bayesian inference

295 and exhibit significant topological discordance among phylogenetic methods [19,22],
296 are both comparatively small (34 taxa, 48 characters and 48 taxa, 82 characters,
297 respectively). These both fall within the scope of simulated datasets that yield low
298 resolution from the Bayesian method and, from other phylogenetic methods, high
299 resolution but low accuracy (figure 1). The two empirical datasets that yield trees with
300 greater congruence from the different phylogenetic methods, are both larger: Luo (114
301 taxa, 497 characters) and Nesbitt (82 taxa, 413 characters). The size of these matrices
302 is comparable with our simulation results in which we see marked increases in
303 topological accuracy and agreement between methods (figure 1 - between 350 and
304 1000 characters).

305

306 **(c) Implications for phylogenetic analysis of phenotypic data**

307 The results of our simulation studies indicate that the cadre of phylogenetic
308 hypotheses generated from phenotypic data using parsimony methods require
309 reassessment using the Bayesian implementation of the Mk model. It is likely that
310 many evolutionary interpretations are contingent on precise but inaccurate
311 phylogenetic hypotheses. In this undertaking it is important that the implications of
312 our simulation studies are considered in the design of phylogenetic studies.

313

314 Firstly, phylogenies of fossils tend toward strong asymmetries [25] and, like all
315 phylogenetic methods, Bayesian inference struggles with the recovery of deep nodes
316 within asymmetric trees. Therefore, it is important that outgroups are sampled
317 extensively, ensuring that contentious in-group relationships are closer to the tips,
318 where topological accuracy is highest. Further, in-group lineages should be sampled
319 in a manner that does not accentuate tree asymmetry.

320

321 Secondly, phylogenetic accuracy and resolution correlates positively with the relative
322 dimensions of the dataset. Accordingly, phylogenetic resolution or certainty should
323 not be expected from cladistic analyses of small morphological datasets (i.e, those
324 around 100 characters or fewer), particularly if they include fossils. There are finite
325 limits to the number of available phylogenetically-informative characters [27] and, for
326 well-studied clades, it may be perceived that these phylogenetically informative
327 characters have already been found. However, it is important to note that the concept
328 of phylogenetic informativeness is different within a likelihood versus a parsimony

framework: in parsimony characters that undergo few changes are prized in favour of homoplastic characters. Under the likelihood model, branch length, informed by the number of character changes, contributes to topology estimation. Thus, traditionally ‘bad’ phylogenetic characters (those exhibiting homoplasy) may find utility in expanding the dimensions of phenotypic character matrices as long as homoplasy falls within the limits that the model can accommodate. In a Bayesian framework this can be tested using posterior predictive tests of model adequacy (e.g. [28]).

Finally, we may need to alter our expectations to anticipate less well-resolved but more accurate phylogenetic hypotheses, which will both constrain and guide research. Greater resolution may be found by generating matrices suited to likelihood- rather than parsimony-based phylogenetic methods. However, we must also come to terms with the prospect that for some groups of organisms, or their fossil remains, there may be insufficient data. As such, their evolutionary relationships might not therefore be resolvable using morphological data alone and, if they are fossils, their evolutionary significance may never be realised. Nevertheless, resolving phylogenies is not the end game for evolutionary biology. Incompletely resolved trees can still be used as a basis for investigating interesting macroevolutionary questions, and methods exist for incorporating tree uncertainty in phylogenetic comparative methods [e.g [29]).

5. Conclusions

A growing consensus shows that the Bayesian Mk model is the most accurate method of phylogenetic reconstruction, and here we show that this remains true across dramatically different tree shapes, when analysing datasets composed of both multistate and binary characters, and when compared to Maximum Likelihood estimation using the Mk model. We would recommend that Bayesian implementations of the Mk model should become the default method for phylogenetic analyses of cladistic morphological datasets, and we should expect low levels of resolution with small datasets. As parsimony methods appear to be less effective than probabilistic approaches, it may be necessary to alter data collection practices by moving away from choosing a selection of characters that undergo few changes, and moving towards scoring all possible characters from the available taxa irrespective of their expected homoplasy.

363

364 **Data Accessibility.** The code used to simulate the data used in this publication can be
365 accessed from Dryad at doi:10.5061/
366

367 **Author’s Contributions.** All authors contributed to the design of the study; MNP and
368 JoR led the analyses; interpretation of results and writing was led by MNP, JoR, PD,
369 and DP, though all authors contributed to the interpretation of results and the writing
370 of the manuscript.
371

372 **Competing Interests.** We have no competing interests.
373

374 **Funding.** This research was funded by NERC (NE/L501554/1 to J.E.O’R. and L.P.;
375 NE/K500823/1 to M.N.P.; NE/L002434/1 to J.F.; NE/N003438/1 to P.C.J.D.),
376 BBSRC (BB/N000919/1 to P.C.J.D.), the University of Bristol (STaR scholarship to
377 A.R.T.), Royal Society Wolfson Research Merit Award (P.C.J.D.) and the John
378 Templeton Foundation (43915 to D.P.).
379

380 **Acknowledgements.** We thank the other members of the Bristol Palaeobiology
381 research group for discussion; Rob Asher (Cambridge) and Thomas Guillerme for
382 comments on the draft manuscript. We also thank April Wright and an anonymous
383 reviewer for their help improving the manuscript.
384

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	Asymmetrical generating phylogeny			
	Equal Weights Parsimony	Implied Weights Parsimony	Maximum Likelihood	Bayesian
100	34.89 (22-56)	37.85 (22-56)	45.84 (20-58)	28.1 (18-39)
350	26.57 (11-51)	29.2 (12-51)	26.49 (6-58)	19.21 (7-35)
1000	17.82 (3-40)	19.16 (2-33)	11.94 (0-58)	9.34 (0-31)
	Symmetrical generating phylogeny			
	Equal Weights Parsimony	Implied Weights Parsimony	Maximum Likelihood	Bayesian
100	8.08 (0-33)	9.29 (0-29)	10.1 (0-58)	7.51 (0-29)
350	1.33 (0-28)	1.43 (0-28)	1.8 (0-52)	1.2 (0-28)
1000	0.32 (0-26)	0.31 (0-26)	0.51 (0-52)	0.31 (0-26)

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Table 1. Bayesian approaches produce the most accurate trees for all character sets. Mean and range (in brackets) of Robinson-Foulds distances are lower for topologies estimated using Bayesian methods for both the symmetrical and asymmetrical generating tree. Maximum Likelihood is the generally the most inaccurate method for the symmetrical generating tree, and implied weights parsimony performs worst for the asymmetrical generating tree.

	asymmetrical tree	symmetrical tree
MB 100	< 0.001	0.09919
Maximum Likelihood 100	< 0.001	0.027295
EW 100	< 0.001	0.106712
IW 100	< 0.001	0.092736
MB 350	< 0.001	0.638242
Maximum Likelihood 350	< 0.001	0.057809
EW 350	< 0.001	0.19683
IW 350	< 0.001	0.148108
MB 1000	< 0.001	0.256976
Maximum Likelihood 1000	< 0.001	0.085987
EW 1000	< 0.001	0.179186
IW 1000	< 0.001	0.287058

Table 2. P Values from Spearman's rank correlation between the percentage of nodes being accurately reconstructed and their distance from the root. Nodes closer to the tips are significantly more likely to be accurately reconstructed in asymmetrical trees but this is not generally true for symmetrical phylogenies.

501 **Figure 1. Contour plots of Robinson-Foulds distance against phylogenetic resolution,**
502 **indicating the higher accuracy of Bayesian implementations against all other methods**
503 **with data generated on the asymmetrical phylogeny.** The spectrum of red to yellow, reflect
504 lower to higher density of trees. As the number of characters increases all methods converge
505 on the correct phylogeny, although Bayesian phylogenies are generally the least resolved. The
506 other methods achieve higher resolution but at a cost of lower accuracy. Data generated on
507 the symmetrical phylogeny shows similar patterns but with much less variance and higher
508 accuracy for all iterations; this lack of variance means point estimates cannot be shown as
509 density estimates.

510

511 **Figure 2. Accuracy of nodes is higher for those closer to the tips in the asymmetrical**
512 **trees.** The percentage of times a node was accurately reconstructed is shown as a proportion
513 of a quarter of a circle in anti-clockwise order for Bayesian, Maximum likelihood, EW-
514 Parsimony, and IW-Parsimony at each node. Accuracy of reconstructions is significantly
515 lower in the 100 character dataset (a), and increases in the 350 character (b), and 1000
516 character datasets (c).

517

518 **Figure 3. Accuracy of nodes is high for all nodes in the symmetrical phylogeny.** The
519 percentage of times a node was accurately reconstructed is shown as a proportion of a quarter
520 of a circle in anti-clockwise order for Bayesian, Maximum likelihood, EW-Parsimony, and
521 IW-Parsimony at each node. Accuracy of reconstructions is high in each dataset size, but
522 there is a non-significant increase in accuracy as dataset size increases (a-c).

523

524 **Figure 4. Alternative phylogenetic reconstruction methods alter our understanding of**
525 **evolution with empirical matrices.** However, the relationship of fossil seed ferns from
526 Hilton and Bateman [19] is changed according to implementation (a-d), although *Caytonia*
527 remains as sister to angiosperms in all analyses. Alternative analyses change the taxonomic
528 affinity of *Kulindroplax* from Sutton et al. [22] (e-h).

529

530 **Figure 5. Alternative phylogenetic reconstruction methods produce generally congruent**
531 **reconstructions of evolution with empirical matrices.** For Luo et al. [20], the relationship
532 between the haramiyids and multituberculates is largely unchanged across analyses (a-d). IW-
533 Parsimony (g) and Bayesian analyses place *Nyasasaurus* as close to the earliest dinosaur (e)
534 and IW-Parsimony places it close to the earliest diverging taxa (g), but EW-Parsimony and
535 Maximum Likelihood place the taxa as a derived member of Dinosauria (f,h).

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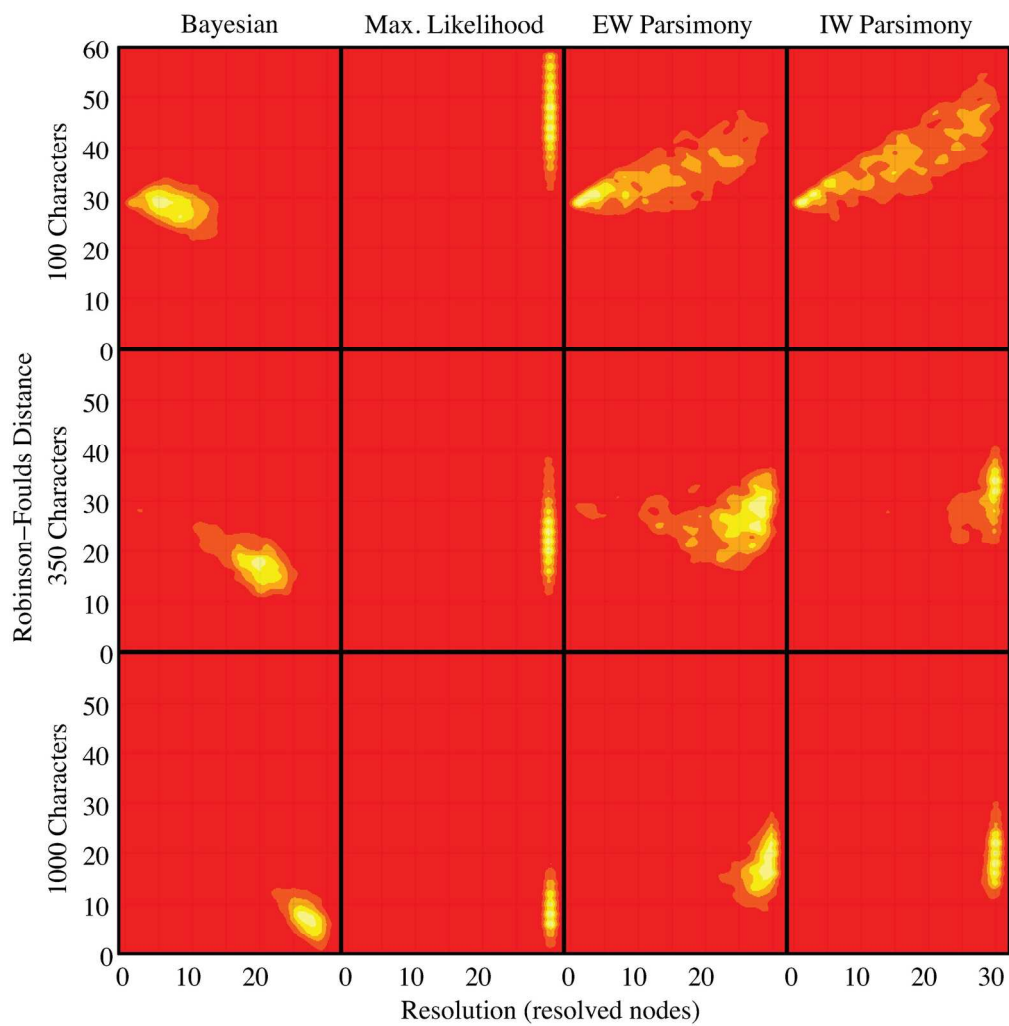


Figure 1

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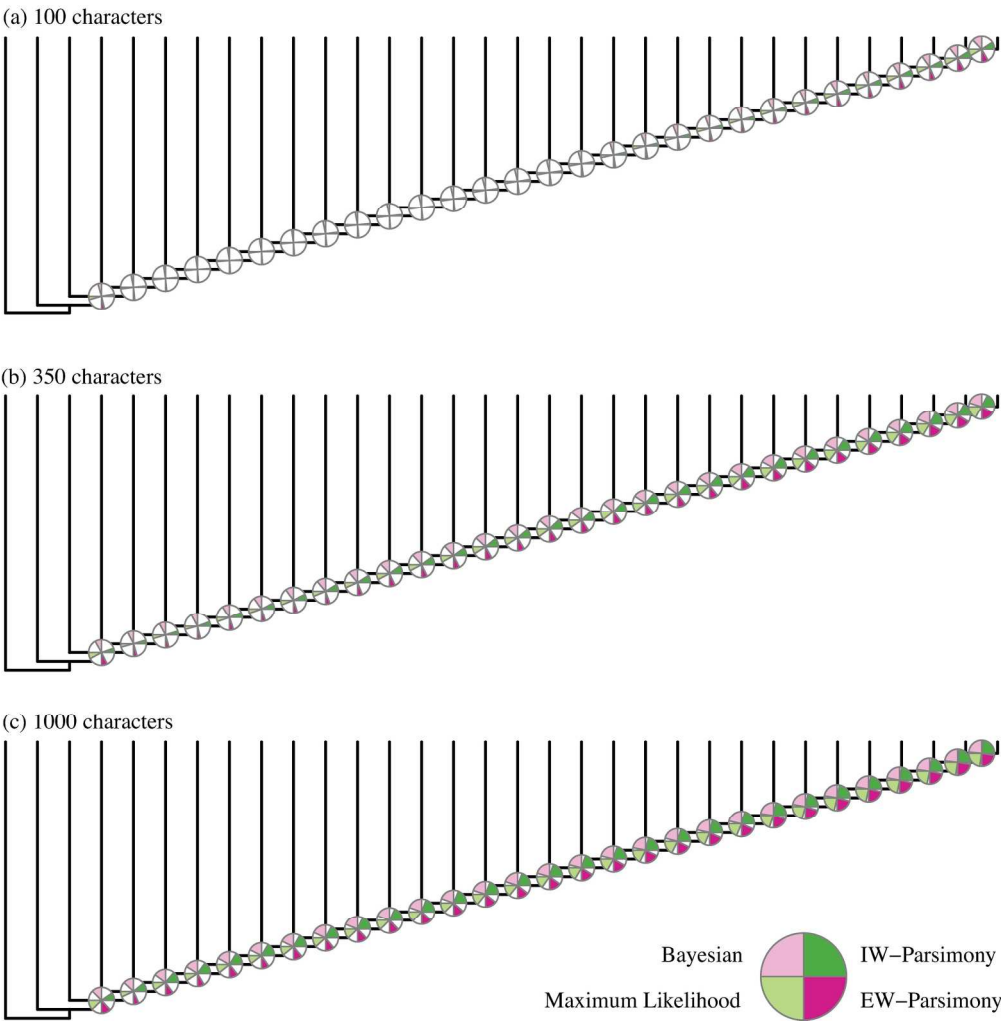


Figure 2

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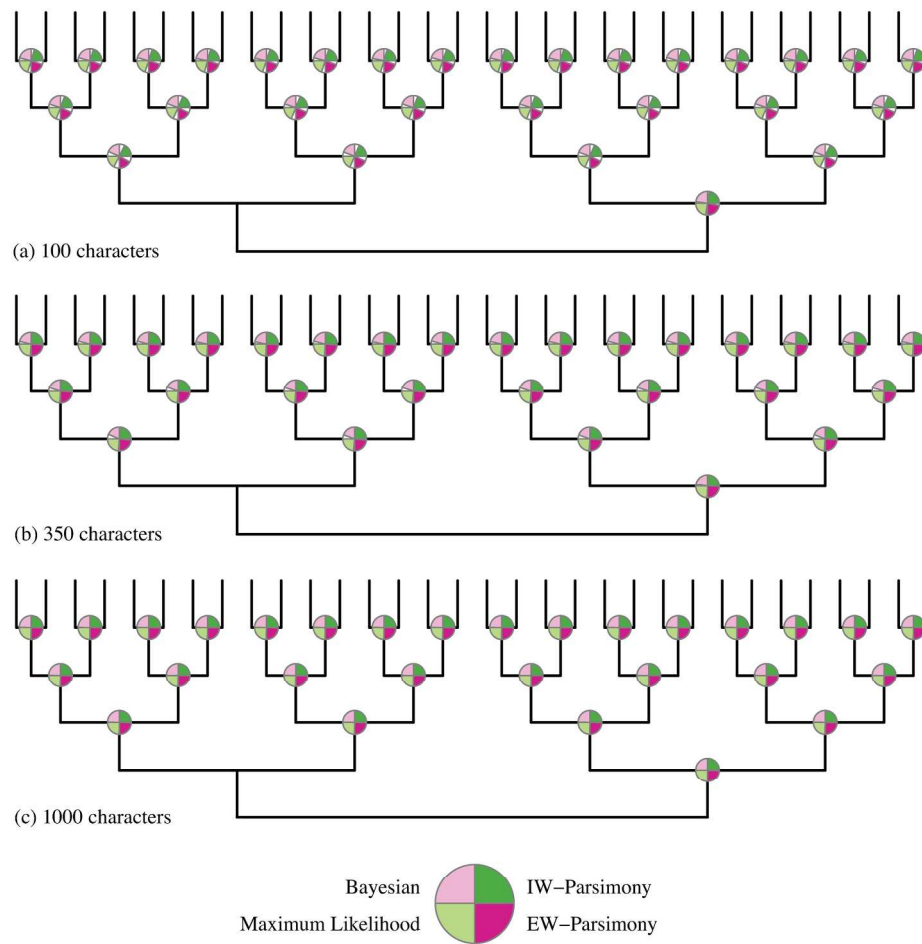


Figure 3

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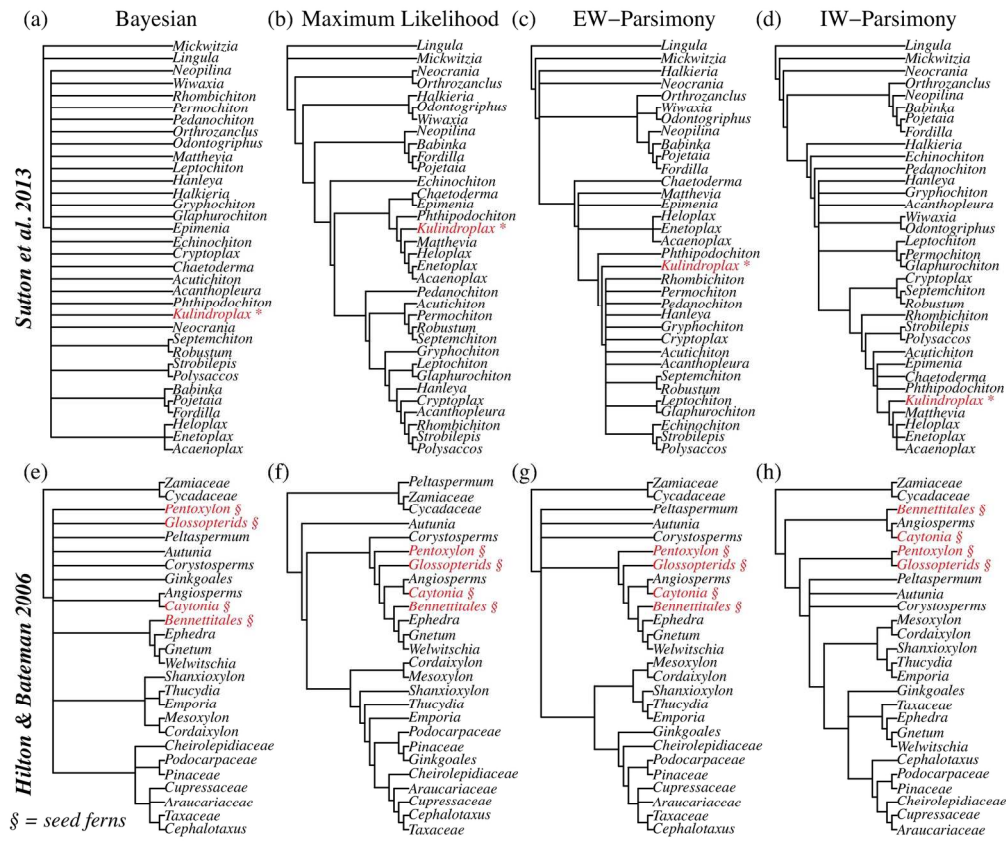


Figure 4

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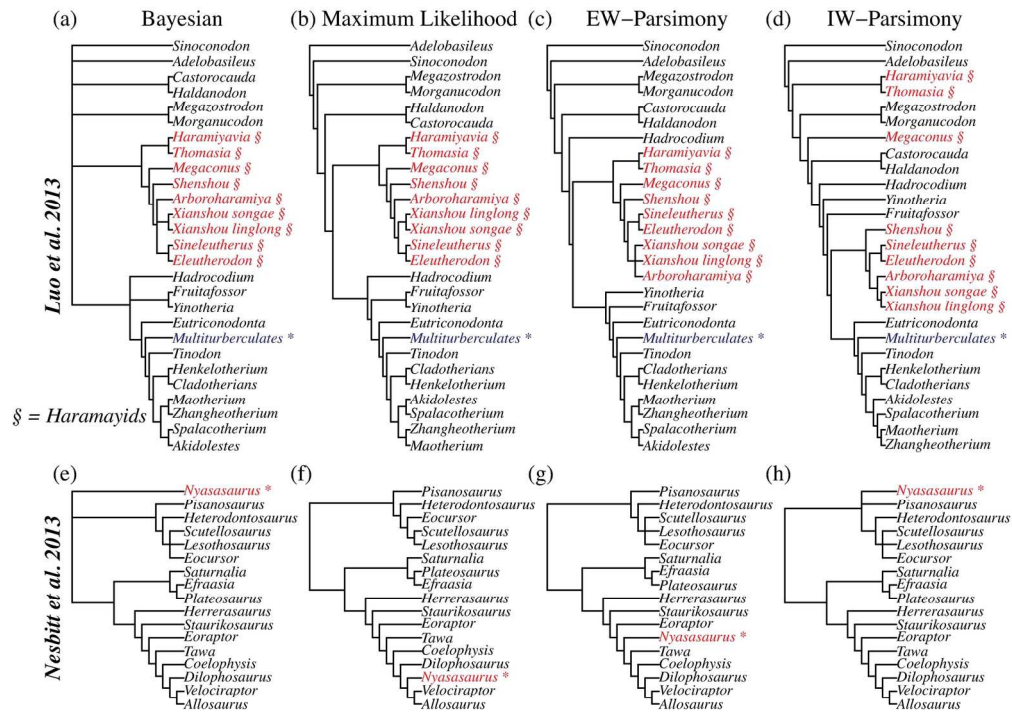


Figure 5

168x149mm (300 x 300 DPI)